

Three Tiers Neighborhood Graph and Multi-graph Fusion Ranking for Multi-feature Image Retrieval: A Manifold Aspect

Shenglan Liu, Muxin Sun, Lin Feng, Yang Liu, Jun Wu

Faculty of Electronic Information and Electrical Engineering,
Dalian University of Technology, Dalian, Liaoning, 116024 China

Abstract

Abstract: Single feature is inefficient to describe content of an image, which is a shortcoming in traditional image retrieval task. We know that one image can be described by different features. Multi-feature fusion ranking can be utilized to improve the ranking list of query. In this paper, we first analyze graph structure and multi-feature fusion re-ranking from manifold aspect. Then, Three Tiers Neighborhood Graph (TTNG) is constructed to re-rank the original ranking list by single feature and to enhance precision of single feature. Furthermore, we propose Multi-graph Fusion Ranking (MFR) for multi-feature ranking, which considers the correlation of all images in multiple neighborhood graphs. Evaluations are conducted on UK-bench, Corel-1K, Corel-10K and Cifar-10 benchmark datasets. The experimental results show that our TTNG and MFR outperform than other state-of-the-art methods. For example, we achieve competitive results N-S score 3.91 and precision 65.00% on UK-bench and Corel-10K datasets respectively.

Introduction

Image ranking has made a number of significant achievements in image retrieval tasks. Ranking methods have attracted increasing attention to image retrieval. In most cases, we usually utilize 1-norm to measure the similarity for statistical histogram of image feature in ranking stage. This direct similarity metric ranking results can be regarded as K-nearest neighborhood (KNN) of query (in re-ranking methods known as a Candidate KNN Set (CKNNS)). However, the K-nearest neighborhood of query is independent to each other, that is, there is no connection between the images of the retrieval results. In general, we assume: *the KNN of query (including query) are similar images and should be related in image retrieval*. This relationship is conducive to the elimination of outlier in the CKNNS, which is conducive to enhance the results of image retrieval. Image re-ranking methods can be developed by CKNNS of query.

This paper focuses on selection of CKNNS and re-ranking for image retrieval by manifold way. Most of previous research only consider the similarity or using graph method to enhance retrieval results. However, image manifold in real

word is always complex, which may not be suitable for image retrieval. Note that *images that are closer¹ to the query image may not have higher correlation with the query image* which is a serious shortcoming of image manifold for image retrieval task. An example is shown in Fig 1.

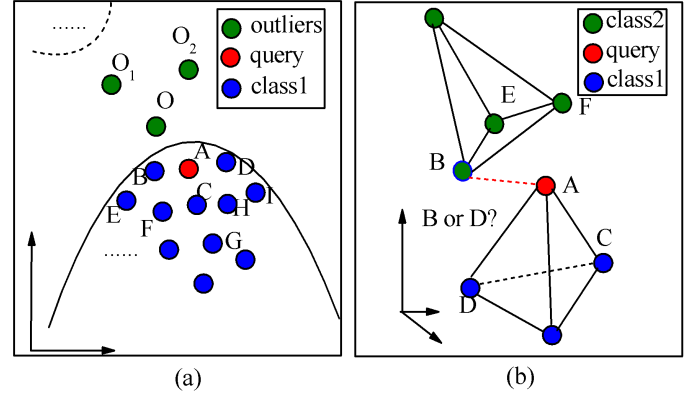


Figure 1: Examples of images that are closer to the query image but have lower correlation with the query image. (a) Outliers are located near the query. (b) The margin of different manifold are close to each other.

Fig1(a) illustrates the influence of outliers on the candidate image set which is constructed by Jaccard coefficient. Given a query image $A \in M$ and image set $\{B, C, D, E, F, G, H, I, O, O_1, O_2\}$, where M is the manifold which query image A located on, and $B, C, D, E, F, G, H, I \in M$. The Jaccard coefficient of two images are presented by J_{ij} , and its weight is w_{ij}^2 , where $i, j \in \Omega$, $\Omega = \{A, B, C, D, O\}$. Denote the neighborhood of image i as N_i which is constructed by KNN method. Then, $N_o = \{A, B, O_1, O_2\}$, $N_A = \{O, B, C, D\}$, $N_B = \{A, O, E, F\}$, $N_C = \{A, F, H, G\}$, $N_D = \{A, C, H, I\}$, $J_{AO} = 3/7$, $J_{AB} = 3/7$, $J_{AC} = 2/8$, $J_{AD} = 3/7$. The candidate image set Ω of query A is constructed by Jaccard coefficient, and is composed of the returned top 5 images.

¹ We use Jaccard coefficient to measure the similarity of images.

² The relationship of two images i, j proportional to w_{ij} , where $w_{ij} = w_{ji}$, w_{ij} can be computed by Jaccard coefficient.

Nevertheless, the result is unreasonable. For the reason that O is not located on M , which means to say O is not correlated to A . Moreover, since $C \in M$ and $O \notin M$, $J_{AC} < J_{AO}$ does not meet the constraint that the candidate image set should locate on the same manifold with A . In Fig1(b), we define two manifolds M_1, M_2 , where $A, C, D \in M_1$, $B, E, F \in M_2$, and assume $w_{AC} > w_{AB} > w_{AD}$ ³ and $w_{DC} + w_{DA} > w_{BC} + w_{BA}$. If the manifold ranking methods of transductive are not taken into consideration and only the distance weights for re-ranking is considered, the retrieval result of A is $A \leftarrow C \leftarrow B$. Clearly, for $A, C \in M_1$, C is a reasonable retrieval result. However, B is an unreasonable result because of $B \in M_2$.

In this paper, we proposed a novel approach for image unsupervised re-ranking of single feature on graph and illustrated rationality of multi-graph fusion ranking by using probability theory. Our image retrieval process can be brief described as follows: (1) KNN of query \rightarrow (2) CKNNS construction by TTNG \rightarrow (3) Multi-feature fusion ranking by MFR. On single feature re-ranking stage, treble tiers neighborhood graph is proposed to improve the ranking list and offer weights of CKNNS. A multi-feature re-ranking method is designed by the weights of improved ranking list. Then, we consider all the images in CKNNS to re-rank the final ranking list, which is different from graph fusion ranking in reference (Zhang et al. 2015)(Bai and Bai 2016). The main contributions of this paper are both on single feature re-ranking and multi-graph ranking stages of images, which are list as follows:

- (1) A novel structure (TTNG) for single feature re-ranking is robust to outlier of CKNNS in most cases.
- (2) Our robust fusion re-ranking method considering CKNNS can enhance the retrieval results with undesirable data distribution.
- (3) We utilize probability theory to illustrate that the retrieval results may be improved while more independent features involved.
- (4) Our method is inductive and efficient for new sample, which need not re-construct neighborhood graph for out-of-sample extensions comparing with transductive ranking method (eg. manifold ranking or multi-graph ranking (Zhao et al. 2014) etc.)

Related Work

Single image feature can only describe an image from a certain view. Such as: HSV (Deselaers, Keysers, and Ney 2008), which can only get the global color information of image, Convolutional Neural Network (CNN) (Krizhevsky, Sutskever, and Hinton 2012) can extract biological features of the image, and the Bag of words (BOW) (Csurka et al. 2004) uses SIFT-based (Lowe 1999) to get the local information and the parts distribution of the image.

In recent years, multi-feature fusion ranking have drawn lots of attentions in information retrieval field. Researches show that graph structure can be extended to multiple features, such as hyper-graph (Huang et al. 2010) and the man-

ifold graph ranking method (Zhao et al. 2014). However, the MR-based methods can only get transductive ranking and low efficiency. In order to solve the above problems, Xu et al. proposed an efficient MR (Xu et al. 2011), which uses clustering techniques to find the landmark and to realize inductive ranking of image datasets. Combined with the above analysis, most of the current MR-based methods require calculation of the KNN for all images, which is a time consuming work. In order to realize efficient inductive ranking, Zhang et al. (Zhang et al. 2015) proposed graph density (GD) re-ranking method based on Jaccard similarity (Levandowsky and Winter 1971). This method only needs to calculate the CKNNS of query, and employs the Jaccard similarity as a judgment basis of nearest neighbor to enhance the single feature image retrieval accuracy. It is worth noting that the proposed method can be easily carried out by multi feature fusion ranking and obtains a more satisfactory result. Bai et al. (Bai and Bai 2016) claim the neighbors in CKNNS contribute equally, which is not a reasonable approach in Jaccard-based method. Sparse Contextual Activation (SCA) is proposed to improve Jaccard-based ranking by Gaussian kernel distance and enhance performance by local consistency enhancement (LCE).

Three Tiers Neighborhood Graph

To enhance the performance in image retrieval, re-ranking is a feasible approach for both supervised and unsupervised methods. As a supervised way, relevance feedback (RF) selects positive/negative samples in CKNNS to construct feedback model. And this procedure should be done for several times. The selection is a non-automatic process in RF. Consequently, unsupervised approaches have attracted attention in recent researches. Zhang et al. proposed graph construction by determining Jaccard coefficient of CKNNS and its neighborhood, which is considered in our graph construction method (TTNG). For simplicity, we substitute “sub-graph” for “graph” in this paper.

Denote a collection of image set $X = \{x_1, \dots, x_n\}$, x^q is the query (or center sample, CS), $N_k(x^q) = \{x_c^q\}$ is the CKNNS of x^q , $c = 1, \dots, k$. CKNNS of x^q is consisted of the k nearest neighbors of x^q under a certain similarity measure and is also the original ranking list which returns top- k images of x^q .

A Brief Review of Single Tier Neighborhood Graph (STNG)

In this subsection, we give a brief review of graph construction re-ranking which only needs the first single tier in reference (Zhang et al. 2015).

The basic idea of the re-ranking method is reciprocal neighbor relation for two different CKNNS of samples which always indicates visual similarity of images (Zhang et al. 2015)(Bai and Bai 2016) and relationship of users in social networks (Jiang et al. 2013). Jaccard coefficient is employed to measure the similarity of $x \in X$ and x^q as follows:

$$J(x, x^q) = \frac{|N_{k_2}(x) \cap N_{k_1}(x^q)|}{|N_{k_2}(x) \cup N_{k_1}(x^q)|} \quad (1)$$

³ If $w_{AB} = w_{AD}$, this case relates to uncertainty learning (Li and Du 2007). This uncertain case can be solved by our method.

The weight of x and x^q is defined by $w(x, x^q) = \alpha J(x, x^q)$, where α is a decay coefficient. The new re-ranking list of x is according to the descendant sorting of w . More details can be referred in reference (Zhang et al. 2015). Bai et al. claim that CKNNS of the query contributes equally in the above process and utilize Gaussian kernel to improve this short coming. However, this approach is not always suitable, which details in reference (Bai and Bai 2016). How to choose a distance function (only using L1-norm or L2-norm etc.) relies on data distribution. In this paper, we only use Jaccard coefficient, and propose a novel structure in re-ranking process in next subsection.

TTNG

TTNG uses Jaccard coefficient to build a weight graph as the first tier. Then based on the first tier, we build the second tier. And we build the third tier based on the second tier. The process of TTNG is described in Fig. 2. TTNG utilizes the neighbors of query on the same manifold to delete the outliers, and solves the problem which is detailed in Fig. 1(a).

As described in STNG, we build the first tier. This motivates us to get the weight of x and x^q by computing the weight $w'(x, x^q)$ of x and x^q as follows

$$w'(x, x^q) = \begin{cases} 1 & (J(x, x^q) > 0) \wedge (x \in N_{k_1}(x^q)) \\ 0 & \text{else} \end{cases} \quad (2)$$

Then, we treat $w'(x, x^q)$ as the weight of the second tier. The weight of x and x^q can be computed by Eq.(3) as follows

$$w(x, x^q) = \sum_{x' \in N_{k_2}(x)} w'(x', x) \quad (3)$$

Finally, $w(x, x^q)$ is regarded as the weight of the third tier.

From the above Eq. (2, 3), we can see that the value of $w(x, x^q)$ is determined by the Jaccard similarity coefficient of nodes in the second and the third tiers. $w(x, x^q)$ in our method is more reliable than that in STNG. To prove our method, we give mathematical expectation of $w(x, x^q)$ as follows:

$$\begin{aligned} E(w(x, x^q)) &= E\left(\sum_{x' \in N_{k_1}(x)} w'(x', x)\right) \\ &= E\left(\sum_{x' \in X} [J(x', x) > 0]\right) \end{aligned} \quad (4)$$

To simply describe the correlation of images, we involve indicator function $C(\cdot, \cdot)$, where $C(x_i, x_j) = 1$ indicates the correlation of x_i and x_j for $\forall x_i, x_j \in X$, otherwise $C(x_i, x_j) = 0$. We also illustrate the relationship between $w(x, x^q)$ and $P(C(x, x^q) = 1)$ by the following assumption: (1) If $J(x, x^q)$ is not zero, x and x^q are correlative, which means $C(x, x^q) = 1$, otherwise x and x^q are not correlative, which means $C(x, x^q) = 0$. (2) Images in $N_k(x^q)$ contribute equally to x^q .

By equation (4), we can express $E(w(x, x^q))$ as follows

$$\begin{aligned} E(w(x, x^q)) &= \sum_{x' \in N_k(x^q)} E([J(x', x) > 0]) \\ &= \sum_{x' \in N_k(x)} E(C(x', x)) \\ &= \sum_{x' \in N_k(x)} P(C(x', x) = 1) \\ &= P(C(x, x^q) = 1 | x \in N_k(x)) \cdot k \end{aligned} \quad (5)$$

By Eq.(5), we can know that the weight function w of this paper is proportional to the probability of similar images. In this subsection, TTNG ranking list can be got by Eq.(3) for image retrieval, which is corresponding to theoretical proof of Eq.(4, 5).

Remark: TTNG can not deal with the problem in Fig 1 (b). This because boundary samples with high relationship (computing by STNG) on adjacent manifolds will not be distinguished by TTNG.

Multi-graph Fusion Ranking

Fusion ranking is an essential approach for multi-feature image retrieval. In this section, we are going to detail MFR method and the basic of MFR theory.

Graph Fusion

In order to obtain the complementary information of image features to improve the accuracy of image retrieval, we need to fuse several features of images. We denote V as node, E as edge and w as weight in image graph. Assuming m features have been extracted from an image. Then m graphs can be constructed by TTNG. In graph fusion methods, the j -th feature graph is defined as $G^j = (V^j, E^j, w^j)$, where $j = 1, 2, \dots, m$. Multi-feature graph can be expressed by $G = (V, E, w)$ which satisfies three constraints as follows: 1) $V = \bigcup_{j=1}^m V^j$; 2) $E = \bigcup_{j=1}^m E^j$; 3) $w(\hat{x}, x^q) = \sum_{j=1}^m w^j(\hat{x}, x^q)$. The fusion process is shown in Fig. 3. From Eq.(5), if the image features are independent in corresponding graph $G^j = (V^j, E^j, w^j)$, according to The Law of Large Numbers and Eq.(5), fusion weight $w(x, x^q)$ satisfies:

$$P(|w(x, x^q) \cdot m - S_p| > \varepsilon) \xrightarrow{m \rightarrow \infty} 0 \quad (6)$$

$$\text{where } S_p = \sum_{1 \leq j \leq m} P(C(x, x^q) = 1 | x \in N_k^j(x^q)) \cdot k.$$

Eq.(6) reflects that, when more independent features are involved, the retrieval results will be better by using this method. By graph construction and fusion method in this paper, we can construct the edge weight function w which is linear to the probability that a pair of images are similar. In next subsection, we will introduce MFR working process for multi-feature image retrieval.

Re-ranking by Multi-feature

We define k images in final retrieval list of x^q as $U_k(x^q) = \{u_1^q, u_2^q, \dots, u_k^q\}$, where $u_1^q = x^q, k = 2, 3, \dots$. If the $k+1$ -th image u_{k+1}^q needs to be added to ranking list, previous

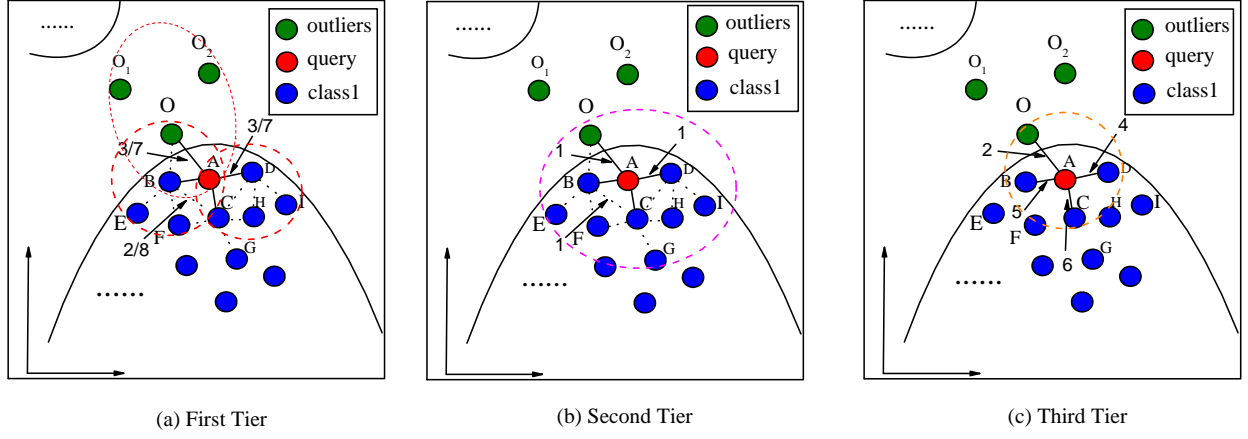


Figure 2: The process of TTNG graph construction

method(Bai and Bai 2016) (Zhang et al. 2015) only considers $w(u_{k+1}^q, x^q)$ which is computed by using Eq.(1), while ours compares the weights from $w(u_1^q, x^q)$ to $w(u_k^q, x^q)$. In MFR, u_{k+1}^q is selected by computing the maximum probability $P_{k+1} = P(C(i, x^q) = 1 | U_k(x^q))$ as follows:

$$\begin{aligned} u_{k+1}^q &= \arg \max_i (P(C(i, x^q) = 1 | U_k(x^q))) \\ &= \arg \max_i \left(\prod_{u \in U_k(q)} P(C(u, i) = 1) \right) \end{aligned} \quad (7)$$

To avoid zero solution in Eq.(7), we modify Eq.(7) to the following expression:

$$u_{k+1}^q = \arg \max_i \left(\sum_{u \in U_k(q)} P(C(u, i) = 1) \right) \quad (8)$$

The final re-ranking results of MFR can be obtained by Eq.(8).

Remark: In our re-ranking method, we assume that *query* and the nearest neighbor of *query* are embedded on the same manifold. If this is not satisfied, the nearest neighbor of query has been deleted by TTNG before (Fig 1(a)).

Experimental results and analysis

This section describes the datasets and features which are used in the experiments in details, and then analyzes the results on each dataset.

Datasets

Four benchmark datasets are utilized to evaluate our ranking method as follows: UK-bench, Corel-1K, Corel-10K, and Cifar-10. Parameters of Datasets (Image Size (IS), Number of Categories (NC), Number of Each Categories (NEC), Total Images (TI)) are detailed in Table 1⁴.

Table 1: Attributes of experimental dataset

Database	IS	NC	NEC	TI	k
Ukbench	640×480	2550	4	10.2k	5
Corel-1K	384×256	10	100	1k	50
Corel-10K	Vary	100	100	10k	50
Cifar-10	32×32	10	6000	60k	50

Image features

The main features used in this paper include: CNN, HSV and SIFT-based, etc..

HSV: HSV color space is popular for image descriptor. For one image, RGB to HSV is a nonlinear transformation. The HSV color space is more suitable for human perception than RGB. HSV color histogram uses 20×10×10 bins for H, S and V components, respectively.

SIFT-based: Each image uses VLFeat-library to extract dense SIFT features of images. SIFT is used to construct BOW and VOC image features by 300 (one image with 1200 dimensional vector generated by tow layers Spatial Pyramid) and 1M vocabulary, respectively.

CNN: We use AlexNet (Krizhevsky, Sutskever, and Hinton 2012) based on convolution neural network structure, and pre-train in the imagenet-1000 dataset for CNN. Finally, we use the L5 value as the CNN feature in image retrieval.

UK-bench dataset

To illustrate the effectiveness of this method in multi-feature graph fusion, this paper combines the single feature methods which are described in this subsection. We compare the retrieval performance of our method with eight competitive methods, including SCC(Takahashi and Kurita 2015), MF(Wang et al. 2012), LGD(Iakovidou et al. 2015), GD(Zhang et al. 2015), SR(Yang, Jiang, and Davis 2015), CBE(Zheng, Wang, and Tian 2014), SCA(Bai and Bai 2016), and AFF(Zhou et al. 2015). The fusion results are shown in Table 2.

⁴In our experiments, we set $k_1 = k_2 = k$.

Table 2: The performance of our method by fusion ranking in Ukbench

Index	TTNG			Ours (TTNG-MFR)			
SIFT-based	✓			✓		✓	✓
HSV		✓		✓	✓		✓
CNN			✓		✓	✓	✓
NS-Score	3.71	3.52	3.51	3.88	3.81	3.89	3.91

Table 3: The N-S score of different methods in Ukbench dataset

SCC	MF	LGD	GD	SR	CBE	SCA	AFF	Ours
3.66	3.68	3.76	3.77	3.78	3.79	3.86	3.88	3.91



Figure 3: The final ranking list for a query example in Ukbench dataset by TTNG-MFR

The results of our method and other state-of-the-art methods in the Ukbench data set are shown in Table 3. Our method achieve N-S score 3.91 in the Ukbench dataset by using global color feature HSV, local features SIFT-based, and deep feature CNN, which is shown in Table 3. This illustrates that the more independent features are involved, the better fusion results are achieved (N-Score=3.91). To illustrate above point of view, a visual retrieval example is conducted as follows: we use an image as query in Ukbench dataset (see Fig. 3). The fusion ranking results of multi-feature which fuse VOC, CNN, and HSV (the last row in Table 2) are better than that of each of single feature (the first three rows in Table 2).

Corel-1K and Corel-10K datasets

In order to show the effects of TTNG-MFR on different datasets, this subsection conducts experiments on the Corel-1K and Corel-10K datasets. We compare the precisions of the first 20 returning images in Corel-1K dataset. We involve seven state-of-the-art image retrieval method, including BFF (Guo, Prasetyo, and Su 2013), ECF (Walia and Pal 2014), SCQ (Zeng et al. 2015), PCM (Yu, Luo, and Lu 2011), CTF (Lin, Chen, and Chan 2009), and GD (Zhang et al. 2015).

In Corel-10K data set, we compare our method with SSH (Liu, Yang, and Li 2015), Ri-HOG (Chen et al. 2015), HOG (Chen et al. 2015), and GD (Zhang et al. 2015) to evaluate our method⁵.

Table 4: The performance of our method in Corel-1K with 20 returns by single feature(%)

HSV	BOW	CNN	method		
			origin	TTNG	Ours
✓			71.67	72.44	74.93
	✓		67.96	68.03	70.22
		✓	57.97	58.80	57.09

Table 5: The performance of our method by fusion ranking in Corel-1K (%)

BOW	HSV	CNN	Ours	
			12-precision	20-precision
✓		✓	89.73	89.01
	✓	✓	76.48	72.41
✓	✓		79.94	76.70
✓	✓	✓	92.43	90.52

Table 7: The precision and recall of different image descriptors and ranking methods with 12 returns in Corel-10K dataset (%)

Type \ method	SSH	Ri-HOG	HOG	GD	Ours
Precision	54.88	53.13	33.29	60.75	65.00
Recall	6.59	6.25	3.94	7.29	7.80

The ranking results for different features are shown in Table 4. As seen in Table 4, the re-ranking precisions of TTNG-MFR can be improved by HSV feature (+3.26%) and is decreased by CNN feature (-0.88%). The different features of the TTNG structure is important to Re-ranking results. Therefore, the higher the accuracy of the original feature is, the better the retrieval performance of the Re-ranking method is.

For multi-feature image retrieval task, the experimental results of TTNG-MFR method are shown in Table 5. As seen from Table 5, the precision of the top 20 images in corel-1K is 90.52% which is the highest precision among fusion CNN, BOW and HSV features in Table 5. Results of our method are consistent with those of UK-bench dataset.

⁵We use HSV, SIFT-based, and CNN features in Corel-10K data set.

Table 6: The precision of previous works and our method with 20 returns in Corel-1K dataset(%)

Methods	Classes										
	African	Beach	Building	Bus	Dinosaur	Elephant	Flower	Horse	Mountains	Food	Avg
BFF	84.70	45.4	67.80	85.30	99.30	71.10	93.30	95.80	49.80	80.80	77.30
ECF	51.00	90.00	58.00	78.00	78.00	100.00	84.00	100.0	84.00	38.00	78.30
SCQ	72.50	65.20	70.60	89.20	100.00	70.50	94.80	91.80	72.25	78.80	80.57
PCM	84.9	35.6	61.6	81.8	100.00	59.1	93.1	92.8	40.4	68.2	71.7
CTF	68.3	54.0	56.2	88.8	99.3	65.8	89.1	80.3	52.2	73.3	72.7
GD	83.75	64.65	67.85	69.55	94.15	83.75	78.45	93.30	85.65	81.05	80.22
Ours	95.25	72.2	82.2	83.55	100.00	95.2	99.05	99.05	91.85	86.8	90.52

Table 8: Performance of different methods in Cifar-10 dataset (%)

Method	BOW	HSV	CNN	12-precision	20-precision	50-precision	100-precision
Origin	✓			47.52	43.62	38.39	35.21
Origin		✓		30.84	27.07	22.85	20.78
Origin			✓	52.91	49.27	44.11	40.68
STNG	✓			47.52	43.63	38.39	35.21
STNG		✓		31.11	27.12	22.52	20.61
STNG			✓	52.93	49.27	44.07	40.64
GD	✓		✓	52.56	48.25	41.15	36.84
Ours	✓		✓	55.33	52.04	47.21	44.22

By comparing the results of Table 4 and Table 5, we can see that our method is suitable for fusion of independent features. Furthermore, In order to illustrate the effectiveness of TTNG-MFR, we compare TTNG-MFR with other methods in corel-10K and corel-1K datasets and give the experimental results in Table 6 and Table 7, respectively.

Cifar-10 dataset

We conduct experiments on the Cifar-10 dataset, and compare precisions of the top 10, 20, 50 and 100 retrieved images to illustrate effectiveness of TTNG-MFR for large-scale image retrieval.

The experimental results from Table 8 show that the single feature re-ranking improves performance little on cifar-10 dataset. This result shows that the re-ranking method does not work well on cifar-10 dataset. By fusing single features in our method, the precision of the top 100 images on Cifar-10 dataset is increased by 3.54%, while that of the graph density method is decreased by 3.84% after fusion ranking, which illustrates that MFR method of this paper is effective and robust to the fusion of independent features. Therefore, TTNG-MFR can obtain high precision and is efficiency for large scale image retrieval task.

Time Complexity

Time complexity of our method on-line correlates with k and m , and especially has no correlation with the size of dataset. The values of k and m are selected based on actual situation. The ranking result of images' single feature in dataset can be calculated off-line. For each image, Re-ranking time complexity is $O(2 \cdot k \cdot \log_2(k))$, time complexity of Jaccard coefficient is $O((m+2) \cdot k^2 \cdot \log_2(k))$, and time complexity of multi-feature fusion is $O((m+1) \cdot k)$.

Thus, the extra time complexity generated by our method is $O((m+2) \cdot k^2 \cdot \log_2(k) + (m+1) \cdot k + 2 \cdot k \cdot \log_2(k))$, which is detailed in Table 9 (Intel(R) Core(TM) i7-4770 CPU @ 3.40GHz 3.40GHz).

Table 9: The Re-rank Time (in ms) on the Test Datasets

Dataset	Ours(ms)	m	k
Ukbench	0.01	3	6
Corel-1k	0.50	3	20
Corel-10k	1.52	3	25
Cifar-10	2.66	2	50

Conclusion

In this paper, we propose two important techniques and demonstrate essential of graph fusion in multi-feature image retrieval task. TTNG can remove the impact of the outlier who is near the retrieval image, which shows the robustness of our method. This strategy can get better results than STNG. Furthermore, MFR can remove the impact of the other classes. As shown in TTNG, although the operation to sum the weights of different features is simple, it is adequately efficient. We evaluate our TTNG-MFR on four benchmark datasets, which demonstrates the effectiveness and efficiency of our ranking method.

In general, fusion re-ranking requires that low-dimensional manifold of each feature maintains structure of original image manifold. If a feature extraction technology destroy structure of original image manifold, better performance can not be obtain by our method. For our further work, we are going to put feature extraction and fusion re-ranking into the same scenario.

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